İstatistikçiler Dergisi: İstatistik & Aktüerya

Journal of Statisticians: Statistics and Actuarial Sciences

IDIA 17, 2024, 2, 46-58

Geliş/Received:22.05.2024, **Kabul**/Accepted: 24.12.2024

Araştırma Makalesi / Research Article

Incorporation of variance calculation differences in reliability predictions

Ongun Yücesan

Atılım Universitesi
Sivil Havacılık Yüksekokulu
Gölbaşı, Ankara, Türkiye
ongun.yucesan@atilim.edu.tr
ORCID: 0000-0003-2263-6803

Abstract

This paper investigates the possible incorporation of the variability of a failure durations observation series into reliability estimates considering failure time series {3, 3, 5, 6, 6.2657} and {2.5097, 4.0678, 4.9942, 5.6460, 6.1684} with very similar mean and variance. The first series of failures of a device would yield the feeling of having a failure in the duration of the third period. Later on, it would have a user experience of failing anytime. The aim of the paper is to investigate how variant conditions can be incorporated into a reliability estimate. For this purpose, distinct schemes were chosen. Initial consideration was the averaging of estimated reliability functions predicted for different deviations. Later considerations involved estimating a single standard deviation figure by averaging possible deviations. Thirdly, is the normalized version of the preceding method. The conclusions drawn from the observations indicate consideration of variability into reliability calculations impacting the estimates, which would be dependent on operational conditions, such as reset costs and safety needs.

Keywords: Mean time between failures, Reliability functions, Reliability estimates

Öz

Varyans hesaplama farklarının güvenilirlik tahminlerine işlenmesi

Makale, arızalar arası süre gözlem serisi varyansının güvenilirlik tahminlerine olası dâhil edilmesini araştırmaktadır. Çok benzer ortalama ve varyansa sahip {3, 3, 5, 6, 6.265} ve {2.5097, 4.0678, 4.9942, 5.6460, 6.1684}hatalar arası süre serileri göz önüne alındığında. Birinci serinin geldiği cihazın arızaları sanki üçüncü periyotta arıza varmış gibi bir his uyandıracaktır. İkinci serinin geldiği cihaz ise sanki her an arıza olacakmış gibi bir kullanıcı deneyimi yaşayacaktır. Bu makale, değişken koşulların bir güvenirlik tahminine nasıl dâhil edildiğini araştırmaktır. Bu amaçla farklı yöntemler seçilmiştir. İlki, farklı sapma değerleri için tahmin edilen güvenilirlik fonksiyonlarının ortalamasının alınmasıdır. Daha sonraki yöntem ise, tek bir standart sapmanın farklı değerlerin ortalaması ile hesaplanılmasıdır. Üçüncü olarak ise, ikinci metot sonucunun normalize edilmesini içermektedir. Sonuç değişkenliğin güvenilirlik hesaplamalarına dâhil edilmesinin, her iş için oluşacak koşullara, sıfırlama maliyetlerine ve güvenlik ihtiyaçlarına göre değerlendirilmesi gereğini ortaya koymaktadır.

Anahtar sözcükler: *Arızalar arasındaki ortalama süre, Güvenirlik fonksiyonları, Güvenilirlik tahminleri*

1. Introduction

For successful operation, users needs to know when a failure is most probable. Many systems, such as aircraft, consist of many electronic components. These are mostly composed of embedded systems and software. To ensure their quality, experiments on reliability are made during the development phase. A healthy duration of operations for the system is used to make reliability predictions [1].

On the other hand, there are limitations for good predictions. In many cases, the virtue of fit tests could result positively [2]. Furthermore, over fit to the available data would mean memorization rather than generalization [3].Therefore, besides basic distribution parameters, additional information about the shape of the underlying histograms is beneficial.

For instance, an overlooked issue is the deviation amount (δ_i) of each sample (x_i) from the simple mean (μ), which is $\delta_i = (x_i - \mu)$. This series represents changes in device behaviour. If the range of samples is limited, it may be simple to define a safe reset period. If they are distributed all around the available sample space, this prediction may be less reliable. The first case can be modeled with a narrow, bell-shaped normal distribution. The second case can be modeled with an exponential distribution. A uniform or a wider shaped normal distribution can as well be considered. These models all have associated errors. For the sake of clarity, comparisons will be performed based on normal distribution assuming similar error margins.

The software can have failures at accumulated or spread time indices. The series from both cases can still result in similar mean and standard deviation. Such a condition represents a hypothetical scenario, emphasizing two different observed characters. These cases could be modeled by the employment of different distributions, with different histogram shapes. However, while samples are few or results are volatile, classical and well known, simple to use distributions are more practical. The aim is to consider different methods of incorporating the deviation amount into reliability predictions by finding ways to represent these scenarios with simple distributions.

The rest of the document is organized as follows: Some bibliographic background, the data, the method of collection of the data and the processes performed on it are described in the first portion of *Section II. Material and Method*, following the brief *introduction in Section I*. to the topic. Section *III. Discussions* includes a comparison of the outcomes of the performed methods. The paper concludes with *Section IV. Conclusions* section.

2. Material and method

This section describes the methodology for observation and incorporation of the deviation amount from reliability observations. First, the techniques related to variance in existing literature are presented. The data set and how it was collected is detailed. Later on, the method of data processing is described.

2.1. Relative history of variance considerations

Variance incorporation is a topic that has been considered in more of a sense that of a developmental item which has a chance of intervention. The recent studies are more limited. The aim was at times minimizing variance RAI et al. [4], at times choosing the minimum variance among an available set of options Yiang et al. [5], or sometimes estimating a lower and upper boundary for the variance of the stochastic process Chadjiconstantinidis et al. [6]. Employment of this measurement for identifying a difference in two forms of the same information and making predictions is also possible, Khieovongphachanh et al. [7]. Deviated cases can be identified and eliminated, Shibo, et al. [8], Abu-Shawiesh [9], Joglekar et al. [10]. There are some fast methods also to estimate these parameters by incorporation of Daubeshie's Wavelet transform Ding et al. [11]. There are employment of deviation metrics for getting around noise and clutter Wang et al. [12]. There are techniques and algorithms that take help from standard deviation to make identifications, detections and improvements to content Yousefpour et al. [13], Zhao et al.[14], Pengsen et al. [15], Prakoso et al. [16], Yang et al.[17]. Some studies consider a deviation to be more significant than others Zhang et al. [18]. Sometimes available samples are limited and prediction of standard deviation may require additional effort Luo [19].

2.2. Data set

The Data Set considered in the study is an array of times to observe a failure series. Those are composed from observations from several test case outcomes and their repetitions. These are performed during a study Yucesan et al. [1] that was already formed into an array during that paper.

All gathered data is over a peer-to-peer industrial workshop electronic Open Platform Collaboration Unified Access (OPC UA) communications. Most of the involved equipment is commercial off the shelf (COTS), while data reading software is modified to the needs from a COTS library. The communication is working in a very similar fashion or being used exactly as in many student rocket probes Matevskaet.al [20] where most of the software and tools are used intact for internal communication of this low-cost vehicle.

2.3. Preparations and methodology for analysis

The method at the beginning involves calculating statistics and probability distribution arrays, then the generation of reliability estimates that are the basis for any safe usage guideline. Whenever the mean μ and the standard deviation σ are at hand, one can generate a cumulative distribution function (CDF). The reliability function is obtained by subtracting CDF (i.e. P(X<x)) from one (1) (see Trivedi et. al. [21]) as in equation (1) and (2). The reliability function is an indicator about chance of proper functioning. Therefore when a failure is probable, before any harm, a reset, repair or a replacement could be made.

$$\mathrm{f}(\mathrm{x}, \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\left(-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right)} \quad where -\infty < x < \infty \tag{1}$$

$$R(t) = 1 - F(\mathrm{x}, \mu, \sigma) = 1 - \mathrm{P(X<x)} = 1 - \int_{-\infty}^{x} f(x, \mu, \sigma) dx \tag{2}$$

Therefore, the probability distribution function (pdf) for variance occurrences is an as crucial component as in equation (1). Gaussian distribution is also considered as being a two parameter one. The read data consists of a bulky accumulated history of 20 counters increasing simultaneously with different step sizes. Algorithmic description of the technique for obtaining a reliability estimate is as follows:

testingMethod()

```
I=0;
while testing
  I=I+1;
  J=0;
  while system working
        Read data
        J=J+1;
  end
  X_i = J;
  Reset
end
```

return X_i

In this algorithm testing Method (), the experiment is conducted till a failure is encountered. The discrete count of repetitions is noted to form series X_i. Read data is not used. The following flow chart in Fig.1 illustrates the prediction technique. The returned value is the observation series X_i. This series is used in the reliability predictions.

Once obtained, the pdf for the variance is incorporated into the reliability estimates. It can be done in a multitude of ways. Nevertheless, three (3) methods have been considered in this study. All methods involve generating a gaussian pdf for considering the variance distribution. This distribution is obtained around the mean of the absolute differences from the "overall mean" of the observation series.

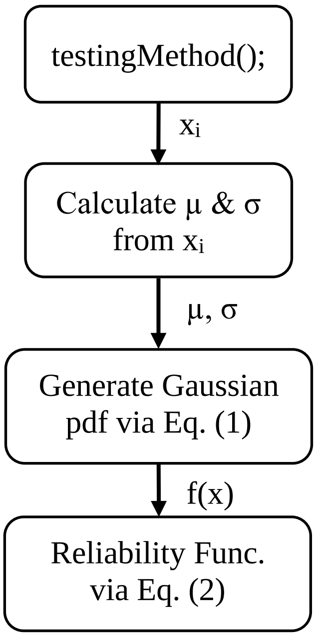

Figure 1. The method for predicting Gaussian Reliability function

Considering the method for calculation of a variance, $\delta_i = x_i - \mu$ we would obtain the aforementioned series denoted as δ_i, namely the series of the absolute differences or as *the variance calculations series*.

Methods are differentiated in how the probability of each deviant value is reflected in the estimation of reliability. For the first technique for incorporating deviance, the Gaussian pdf obtained from the variance series is reflected onto the standard reliability function by calculating the weighted average of the Normal normalized distributions for each possible variance value. Over the alternative approaches, calculating this mean value corresponds to the multiplication of the individual possible variance value's distribution in an interval with their corresponding probability of occurrence from the variance series pdf, which can be deemed as a weighted expectation as in equation (4) where $p_{dev}(x)$ is as in equation (3) representing the histogram of variance calculation series in absolute terms using Gaussian pdf of Equation (1). $\mu_{variance}$ *and* $\sigma_{variance}$ are mean and standard deviation obtained from the absolute values of the series δ_i.

$$p_{dev}(\delta_i) = f(|\delta_i|, \mu_{variance}, \sigma_{variance}), \qquad \delta_i \in \left[\mu_{variance} - \frac{\sigma_{variance}}{2}, \mu_{variance} + \frac{\sigma_{variance}}{2}\right] \quad (3)$$

$$\overline{R1(x)} = 1\text{-}\sum_{\forall\delta_i} F(x, \mu, \delta_i).p_{dev}(\delta_i)\ , \quad \delta_i \in \left[\mu_{variance} - \frac{\sigma_{variance}}{2}, \mu_{variance} + \frac{\sigma_{variance}}{2}\right] \quad (4)$$

The second technique comes with a single variance or standard deviation (σ) figure to generate the final reliability function as in equation (5).

$$\overline{R2(x)} = 1 - F(x, \mu, \sum_{\forall\delta_i} \delta_i.p_{dev}(\delta_i)), \quad \delta_i \in \left[\mu_{variance} - \frac{\sigma_{variance}}{2}, \mu_{variance} + \frac{\sigma_{variance}}{2}\right] \quad (5)$$

The final method is to normalize this generated estimate reliability function with its maximum to obtain a function starting from one as in equation (6).

$$R3(x) = \overline{R2(x)} \Big/ \max(\overline{R2(x)}) \quad (6)$$

The paper attempts to identify differences in reliability estimates based on the inclusion of the variance technique. The variance series mean $\mu_{variance} = 133.8776$ and the standard deviation of this series is $\sigma_{variance} = 160.2485$. The pdf generated over these parameters is as in Fig. 1. There is a small issue which is the total sum of all probabilities over the mentioned interval $\left[\mu_{variance} - \frac{\sigma_{variance}}{2}, \mu_{variance} + \frac{\sigma_{variance}}{2}\right]$ is one. The operation corresponds to slight over-normalization rather than division by the sum over the interval $[+\infty, -\infty]$. This normalization is required to satisfy any random variable's pdf conditions.

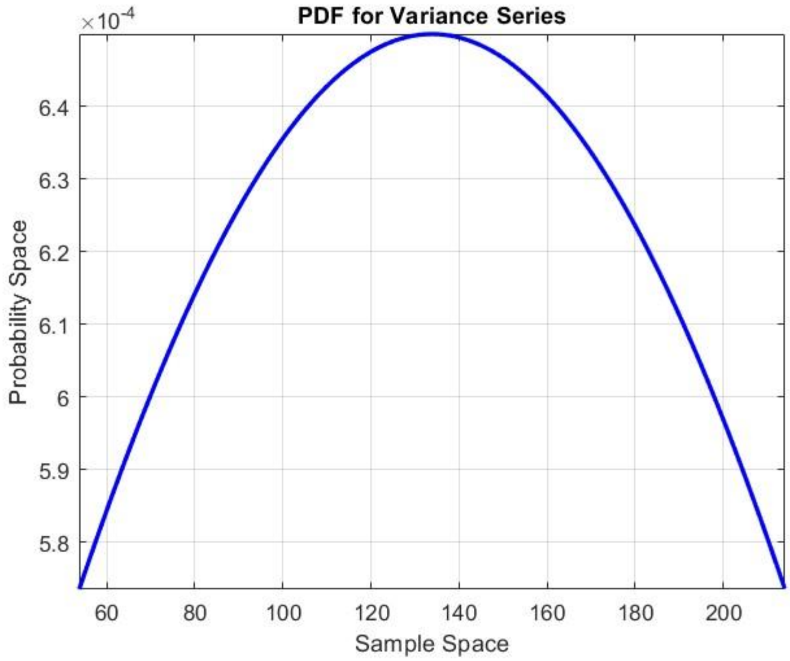

Figure 2. The Gaussian pdf estimated for the variance calculation series

The observation series employed to obtain the statistics (i.e. mean and variance). Using this information a Gaussian distribution is formalized. This approach predicts probability of occurrence. The resulting pdf for variance calculation series is visible from Fig.2.

2.4. Highest and lowest variance generated PDFs

One can see from Fig.3 that the domain of the histogram for collected data is the same interval as the variance calculation series. In this figure the highest encountered deviation observation is used as the deviation parameter for pdf, next to the minimal deviation pdf. The lighter-colored curve is with maximum deviation and is not grouped at the center. So the wings of the histogram are wider. In contrast to the low deviation, a tendency to uniform nature exists. In this case, every outcome is equally possible rather than a common time of arrival for error. Whereas with low variance pdf, most of the outcomes would have been coming from samples nearby the mean.

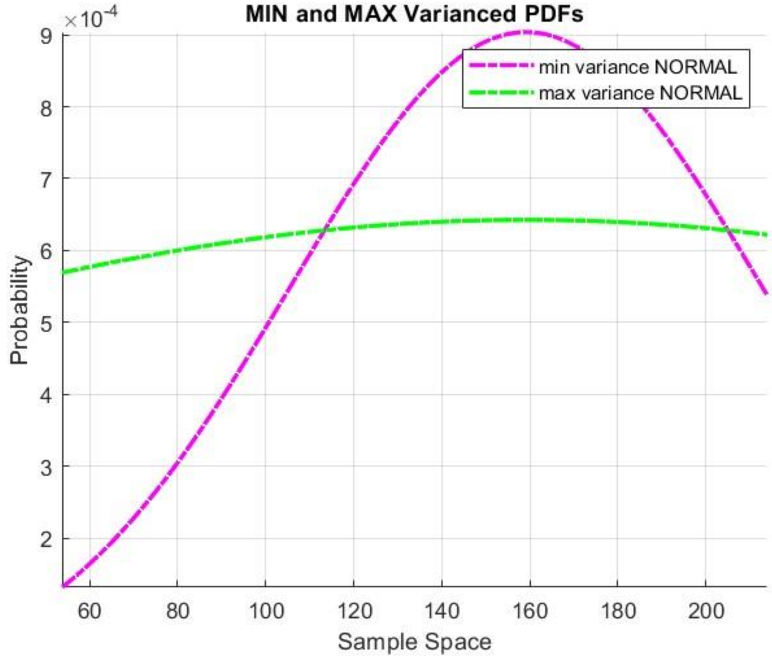

Figure 3. The Gaussian PDFs for minimum considered variance and maximum considered variance

2.5. PDFs for observations and variance calculation series

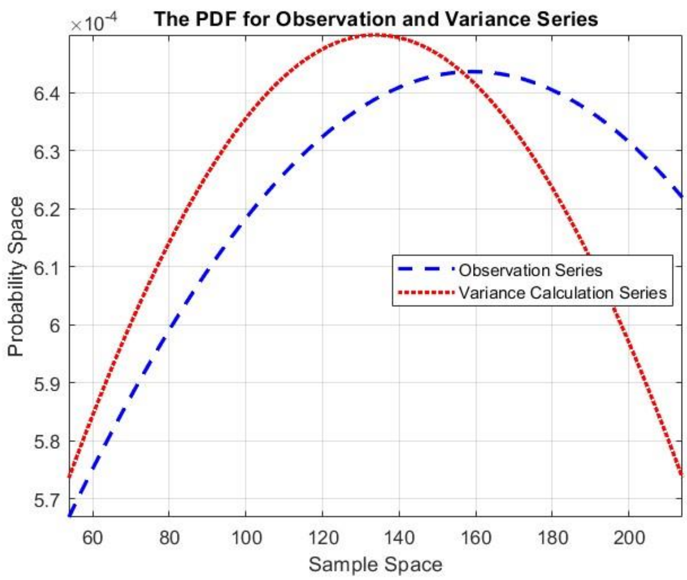

Figure 4. The PDFs Distribution predictions for originating series and variance calculation series

From Fig. 4, expresses Gaussian histograms for observed data (dashed line) and the variance calculation series δ_i . They have different means; the original series is with parameters $\mu_{original} = 159.1885$ and $\sigma_{original} = 209.1672$. Later it had, as previously mentioned,$\mu_{variance} = 133.8776$ and $\sigma_{variance} = 160.2485$ with respective order of the parameters.

2.6. Method of weighted sum of the CDFs for all sample space

This section presents the results of the first method, calculating the weighted average over histograms using each deviation amount used as second parameter for Gaussian reliability functions.

Fig. 5 shows the low-variance prediction at the highest position. It has most of the energy accumulated around the mean. In contrast, high-variance series looks like a straight line placed at the lowest position. The Weighted Average by increments of 0.1 in the interval $\left[\mu_{variance} - \frac{\sigma_{variance}}{2}, \mu_{variance} + \frac{\sigma_{variance}}{2}\right]$ is presented with evident dashed lines in the middle of both curves. It carries some of the impact of the accumulated energy of the lowest variance series and the wide wings of the highest variance series. Here the CDFs used to generate the R(x) estimates are normalized. This causes the series to start and end with similar points due to the R(x) = 1-CDF(x) operation. Their starting point is therefore very similar but different mean and deviations are the case. This figure indicates, under the conditions expressed, employing the first method gives a more curved character to reliability prediction without being as curvy as minimum deviation.

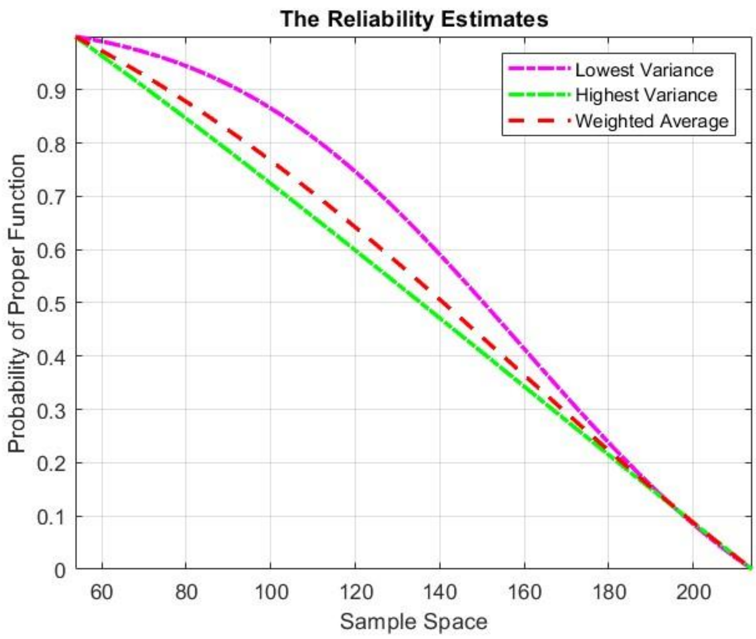

Figure 5. The Reliability Estimates of Highest, Weighted Average, Lowest variance figures from left to right

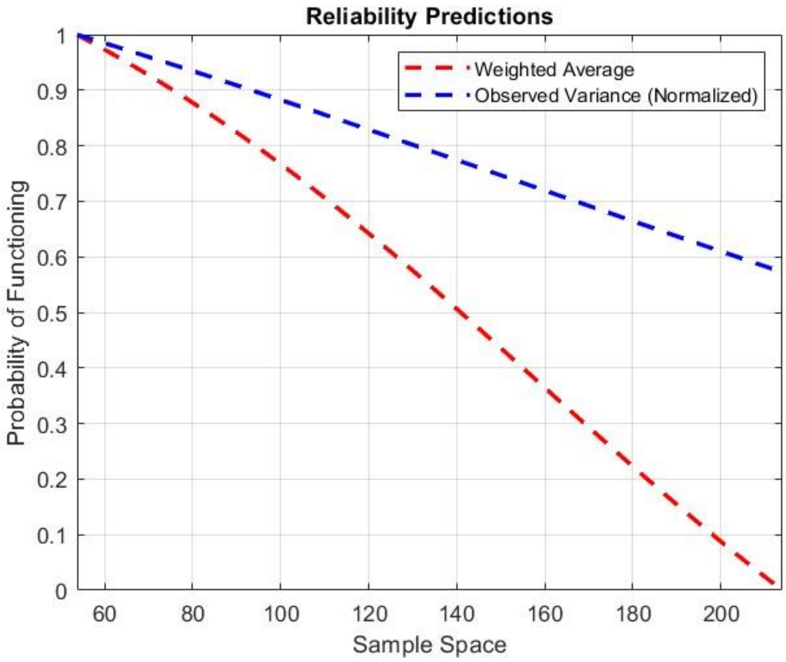

Figure 6. Normalized Observation Series Reliability Estimate and obtained Weighted Average Rel. Estimate

In Fig. 6, there are two estimates. The higher residing curve is the estimate obtained by simply using the mean and variance from the observation series normalized with its maximum value starting from one. Matlab function was used in this case. The lower residing one is the weighted average series from Fig.5.

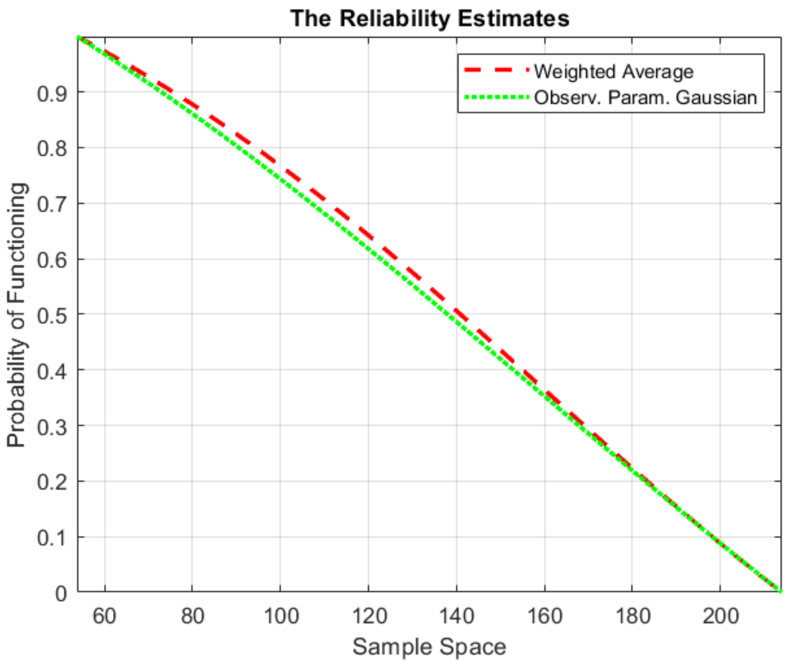

Figure 7. Observation Series Reliability Estimate and obtained Weighted Average Rel. Estimate as from same method

Fig. 7.illustrates a comparison based on Gaussian reliability estimates with classical standard deviation obtained from the original (dotted) and as the alternative weighted average (dashed) series. It presents more curvature in the weighted average case because of the contributions of low-

variance estimates. The high-variance reliability functions are flat with little impact. Therefore, the weighted average predicts the reliability higher, at risk to the customer. The harm that can take place during maintenance activities might justify such a condition.

2.7. Method of weighted averages for deviations

In this case, rather than averaging the sum of the squares and then calculating the square root for this value as in a variance calculation, 1_{st} norm of variance calculation series is divided by its series length. So this figure is not variance, not standard deviation, but a smaller or equal value. Considering an all absolute of one (1) deviations case, standard deviation and 1_{st} norm divided by length would be equal. Since this case is not the situation and the deviations are greater than one (1), and since integers are the case, the 1_{st} norm divided by length yields a smaller value. This smaller value can be regarded as an average standard deviation (STD) figure obtained and used for Gaussian pdf as the second parameter. It is in actuality the median of the variety. The first being 133.8553 later being 133.7533. If the higher median was used, they would actually be the same.

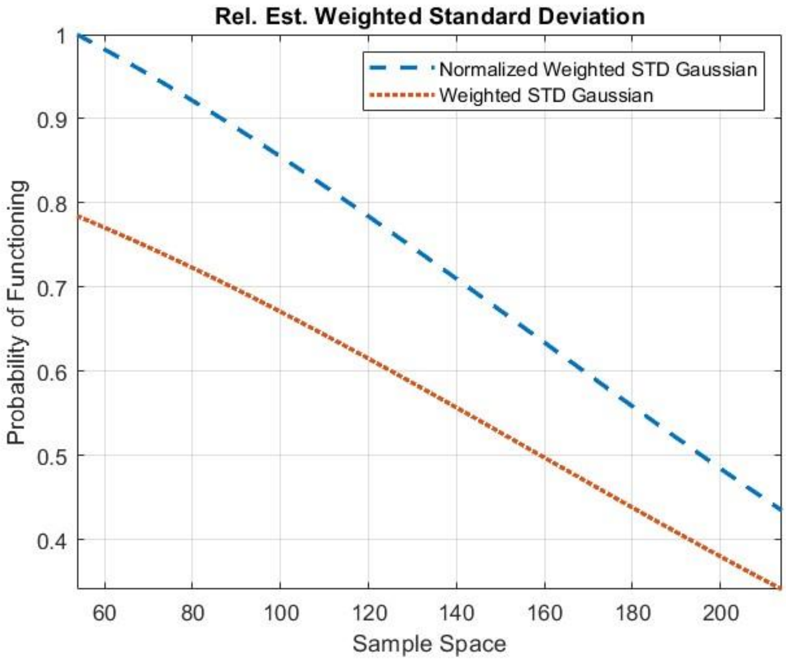

Figure 8. The average (mean) STD calculated by weighing with the probability of the individual sample

Fig.8, illustrates the single average deviation figure obtained from second and third methods. Two different graphs are visible: the dotted line represents the direct and the dashed line represents the normalized estimations.

2.8.The reliability estimate calculated with total sum normalization

In Fig. 9, during the outline of experimentation, the outcome of the first and third methods is also included. The second method is avoided in the figure also due to low start point. The exponential is seen among these reliability estimates according to its mean generated by MATLAB function. Minimum variance curve is the highest residing one, and the dashed line below that is the curve of the first method. The light coloured dotted line is the curve of the third method. The highest deviation curve is one of the lower parts of the group, with slightly darker dotted lines. This curve has second parameter (classical standard deviation) slightly less than the maximum deviation (213.95) with $\sigma_{original} = 209.1672$. The solid curve starting from 0.7 is the exponential curve reliability estimate.

It is rapidly falling in early samples; however, it is relatively constant after a while as samples progress.

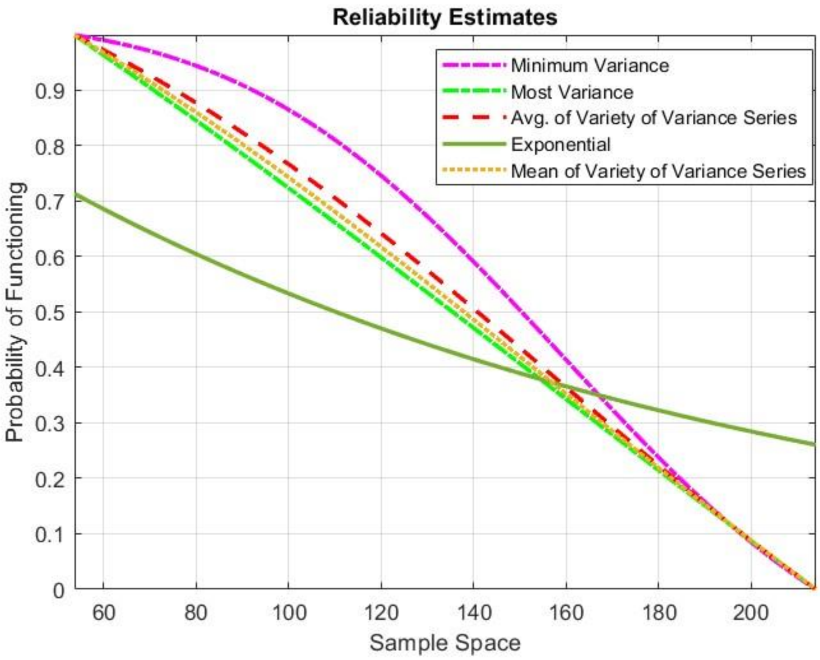

Figure 9. The Exponential along with the variety of reliability estimates

3. Discussions

The figure that drives the discussion mainly is Fig. 9, since it is the figure comparing the normalized estimates of reliability together. Exponential was not normalized in this case for the sake of relevance to common theory. Fig.10 indicates the similar not normalized version starts around 0.85 in the experiment domain starting from 60. The low deviation estimates stay around level 1 for a while. However, the weighted average case (first method) indicates a shift towards a low-variance scenario as an alternative to relatively flat estimate of the high variability. Such an understanding shows that the risk is to the customer if low variability is considered for early values. Considering the cost for repairs and maintenance risks, such an alternative can be handy at the times these factors are relevant. It may the case where the devices are at remote locations that are hard to reach.

In cases where the reset has the probability of causing additional safety hazards or failures, there would be a trade-off. A reset requires some intensive activities. These can also cause the processor to overwork, heating it to the extent that it may not function anymore or for a while at least.

Fig.10, illustrates a MATLAB generated comparison for high variance and low variance scenarios. In this figure, the "extended duration usage case" is clearly visible. In long duration, low variance calculates the reliability lower. In that situation, it enables safer usage predictions for reset periods. When the usage is extended the functioning probability is already less than 50%. If such consideration turns out to be necessary, the lesser the distributed results the safer the predictions.

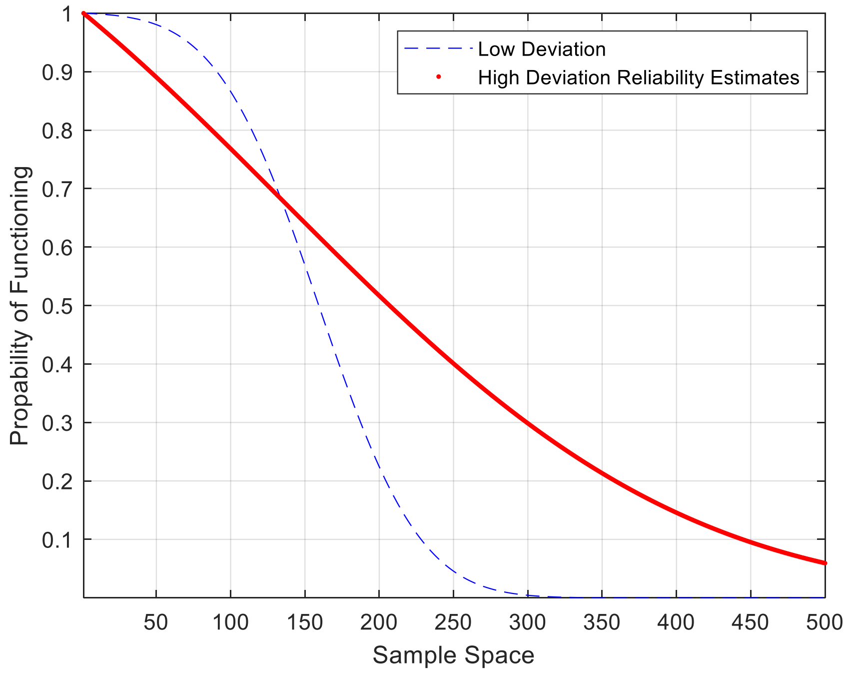

Figure 10. The Gaussian Reliability Estimates with highest and lowest deviations.

Gaussian is more useful for estimates around mean values [2] such as MTBF. It could be possible to compare other distributions with variance, but Gaussian is sufficient for a fair comparison. They were based on the impact of different deviation amounts by normalizations. It is notable that the differences are not strong enough to justify for pure reliance on any proposed method. A logical path for resolving this issue is to consider the situation with available data. The study makes comparisons under similar conditions/methods of estimations, aiming to guide such considerations. The comparison is for cases, where the purpose is to predict a safe reset period. Obviously, any product with lower variance is safer for any usage scenarios. However, a safer period to reset is using the highest variance possible.

The methods proposed may not be useful for safety critical considerations. Being ignorant of possible high-variance scenarios may lead to underestimating problems. The chance of failure is distributed over time. In such a case, if possible, improvements to system would be helpful. However, under the scenarios available, safest usage is with consideration if a high variance exists. This consideration comes at a price of making a reset cost. If it can be formulized, it can further be a good decision problem as a future work. Watching the chances of a failure taking place for a reset, using higher variety estimates might come in handy assuring the highest safety per users.

4. Conclusions

Simply averaging the reliability predictions can be handy whenever cost for a reset is significant. It is essential to take into account the operational needs and the deviant conditions for reliability estimates. For a reset period identification, using higher variety estimates is beneficial assuring the highest safety per users.

References

[1] O. Yucesan , A. Ozkil ve E. Ozbek , “A Reliability Assessment of an Industrial Communication Protocol on a Windows OS Embedded PC for an Oil Rig Control Application” in Journal of Science, Technology and Engineering Research, c. 2, volume.2, pages. 22-30, Dec. 2021, doi:10.53525/jster.971534

[2] O. Yucesan , A. ̇Ozkil ve M. E. ̇Ozbek , “Validity of Exponential Distribution for Modelling Inter-failure Arrival Times of Windows based Industrial Process Control Data Exchange” inJournal of Science, Technology and Engineering Research, c. 3,Volum. 1, pages. 1-8, june. 2022, doi:10.53525/jster.1017004

[3] L. Wang, O. Thakkar and R. Mathews, "Unintended Memorization in Large ASR Models, and How to Mitigate It," ICASSP 2024 - 2024 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Seoul, Korea, Republic of, 2024, pp. 4655-4659, doi: 10.1109/ICASSP48485.2024.10446083.

[4] A. Rai, R. Valenzuela, B. Tuffin, G. Rubino, P. Dersin ”Approximate Zero-Variance Importance Sampling for static network reliability estimation with node failures and ap-
plication to rail systems.” Conference: 2016 Winter Simulation Conference (WSC) December 2016, 3201-3212.10.1109/WSC.2016.7822352.

[5] Y. Jiang, J. Lin, B. Cukic and T. Menzies, ”Variance Analysis in Software Fault Prediction Models,” 2009 20th International Symposium on Software Reliability Engineering, Mysuru, India,2009, pp. 99-108, doi: 10.1109/ISSRE.2009.13

[6] StathisChadjiconstantinidis, ”Some bounds for the renewalfunction and the variance of the renewal process,” in Applied Mathematics and Computation, Volume 436, 2023, 127497, ISSN 0096-3003, https://doi.org/10.1016/j.amc.2022.127497

[7] V. Khieovongphachanh, S. Kanthavong, K. Hamamoto and M. Chanthavong, "Image quality criterion of ultrasonic echo image using Standard Deviation," The 4th Joint International Conference on Information and Communication Technology, Electronic and Electrical Engineering (JICTEE), Chiang Rai, Thailand, 2014, pp. 1-3, doi: 10.1109/JICTEE.2014.6804082.

[8] S. Xin, Y. Wang and W. Lv, "Standard deviation control chart based on weighted standard deviation method," Proceedings of the 33rd Chinese Control Conference, Nanjing, China, 2014, pp. 3574-3579, doi: 10.1109/ChiCC.2014.6895533.

[9] Abu-Shawiesh, Moustafa. A control chart based on robust estimators for monitoring the process mean of a quality characteristic. International Journal of Quality & Reliability Management.(2009) 26. 480-496. 10.1108/02656710910956201.

[10]P. Joglekar, T. Katale, A. Katale, S. Deshpande, A. Nirgude and A. Chotrani, "A Novel approach for formation of Dense Clusters by Outlier Elimination and Standard Deviation," 2024 Fourth International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT), Bhilai, India, 2024, pp. 1-6, doi: 10.1109/ICAECT60202.2024.10468952

[11] F. Ding and T. Cao, "Application of Daubechies Wavelet Transform in the Estimation of Standard Deviation of White Noise," 2011 Second International Conference on Digital Manufacturing & Automation, Zhangjiajie, China, 2011, pp. 212-215, doi: 10.1109/ICDMA.2011.59.

[12] Y. Wang, C. Zheng and H. Peng, "Covariance Mean-to-Standard-Deviation Factor for Ultrasound Imaging," 2020 IEEE International Ultrasonics Symposium (IUS), Las Vegas, NV, USA, 2020, pp. 1-4, doi: 10.1109/IUS46767.2020.9251390.

[13] A. Yousefpour, R. Ibrahim, H. N. Abdul Hamed, U. H. Hair Zaki and K. A. Mohamed Khaidzir, "Feature subset selection using mutual standard deviation in sentiment mining," 2017 IEEE Conference on Big Data and Analytics (ICBDA), Kuching, Malaysia, 2017, pp. 13-18, doi: 10.1109/ICBDAA.2017.8284100.

[14] L. Zhao, L. Wang and D. Liu, "Hyperspectral Imagery Band Selection Based on Maximal Standard Deviation," 2015 8th International Symposium on Computational Intelligence and Design (ISCID), Hangzhou, China, 2015, pp. 59-62, doi: 10.1109/ISCID.2015.141.

[15] K. Pengsen and Y. Zhenming, "Image blurred region detection based on RGB color space information and local standard deviation," 2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), Chongqing, China, 2017, pp. 2177-2181, doi: 10.1109/IAEAC.2017.8054403.

[16] B. S. Prakoso, I. K. Timotius and I. Setyawan, "Palmprint identification for user verification based on line detection and local standard deviation," 2014 The 1st International Conference on Information Technology, Computer, and Electrical Engineering, Semarang, Indonesia, 2014, pp. 155-159, doi: 10.1109/ICITACEE.2014.7065733.

[17] Yang and Zheng Zhou, "Research and implementation of image enhancement algorithm based on local mean and standard deviation," 2012 IEEE Symposium on Electrical & Electronics Engineering (EEESYM), Kuala Lumpur, 2012, pp. 375-378, doi: 10.1109/EEESym.2012.6258668.

[18] J. Zhang, "Study on Software Project Significant Deviation Standard," in Computer Science and Software Engineering, International Conference on, null, 2008, pp. 15-18, doi: 10.1109/CSSE.2008.721.

[19] W. Luo, "A comment on "Estimating the standard deviation from extreme Gaussian values"," in IEEE Signal Processing Letters, vol. 12, no. 2, pp. 109-111, Feb. 2005, doi: 10.1109/LSP.2004.840840.

[20] Matevska, Jasminka &Noack, Enrico & Reinhold, Manuel &Diekmann, Eike. (2020). Decentralised Avionics and Software Architecture for Sounding Rocket Missions. 10.18420/SE2020_66

[21] K.S. Trivedi Probability & Statistics With Reliability, Queuing And Computer Science Applications, 2Nd Ed Wiley India Pvt.Limited, 2008, isbn 9788126518531 Conference Proceedings